A MULTIRESOLUTION SPECKLE REDUCTION ALGORITHM WITH APPLICATION TO SAR IMAGES

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ABSTRACT

Synthetic Aperture Radar images are the representation in range and azimuth coordinates of the signal received by a radar system exploring a portion of the earth surface. The speckle reduction technique presented in this paper takes advantage of the knowledge of the statistical model of the backscattered signal to design a wavelet thresholding scheme, appropriate for this particular type of noise. Before the application to actual images, the algorithm validity has been tested by comparison with the Wiener filter, performed on random sequences generated according to the backscattering statistical model.

1 INTRODUCTION

Speckle noise associated with Synthetic Aperture Radar (SAR) images reduces image understanding and the ability to extract useful information from the backscattered signal. The knowledge of a model for the SAR image is essential in the design of appropriate speckle reduction techniques. The statistical description of the radar backscattering process, where speckle is a multiplicative noise, has been used in the literature to develop different algorithms to improve SAR image quality [1, 2, 3].

The aim of reducing the speckle without significant resolution loss can be achieved by a multiresolution SAR signal representation using the wavelet transform [4], which allows the extraction of information from the different spectral bands discriminating between signal and noise based on their different spectral properties.

A scheme for additive Gaussian noise reduction, based on thresholding the wavelet coefficients, was presented in [5] and its application to SAR images can be found in [6]. In this paper a new technique is developed which applies to non-Gaussian noise with an improved thresholding scheme. The new algorithm will be shown to give an estimate of the information signal which is very close to the estimate obtained by means of a Wiener filter for simulated data sets. The performance of the new algorithm will also be compared to the method described in [6] for actual ERS-1 SAR images.

2 RADAR BACKSCATTERING

The coherent signal backscattered from a surface scanned by the radar system can be represented, from the statistical point of view, as a doubly stochastic process [7, 2]:

$$z(m,n) = s(m,n)g(m,n) \tag{1}$$

wherein $s(\cdot)$ is a modulating component, independent of the wide band Gaussian complex process $g(\cdot)$, and (m,n) are the range-azimuth coordinates. In particular, a SAR image is a representation of the intensity of Eq. 1, where the speckle comes from the Gaussian process, resulting in a multiplicative noise, with an exponential probability density function (pdf), which covers the scene (texture). An important correlation property of the signal $z(\cdot)$ is that the modulating component decorrelates on a much longer time scale than the correlation time of the Gaussian component or, equivalently, the speckle spectrum is much wider than the texture one [7]. This property is particularly important in a multiresolution analysis, since signal and noise will have significantly different spectral bands.

3 MULTIRESOLUTION SPECKLE REDUCTION ALGORITHM

Multiresolution signal representation is a mathematical tool providing a hierarchical framework for analyzing the signal information at different resolutions. In particular it is useful in image analysis where the details at different resolutions generally characterize different physical structures of the scene. In [4] Mallat presented the multiresolution analysis of a n-dimension signal as its decomposition on a wavelet orthonormal basis of $L^2(R^n)$, built by dilations and translations of a unique function called *mother wavelet*. The orthogonal wavelet representation of a discrete signal consists of a reference signal at a coarse resolution and a set of detail signals at finer and finer resolutions; it can be realized by using pyramidal algorithms with a cascade of low-pass and high-pass filters [4, 8].

The wavelet based method described in [5] for the reduction of additive white Gaussian noise considers that, after an orthonormal transformation of the noisy signal, every wavelet coefficient contributes noise of the same variance, but only a few wavelet coefficients contribute to the signal. The signal information is present in the coarse resolution level (low frequency band) and in the wavelet coefficients corresponding to the rapid signal variations in the time domain. Thresholding rules [5, 6] are used that retain only observed data exceeding a multiple of the noise level. It is worth noting that the noise level in the wavelet coefficients is the same at every resolution level only if the transformation is orthonormal and the noise is white.

The coherent radar backscattering model is given by Eq. 1, resulting in an image corrupted by multiplicative noise with an exponential pdf. Following the homomorphic filtering approach given in [9], the speckle reduction problem can be restated as a denoising problem in an additive noise environment where, due to the statistical properties of the backscattered signal, the noise has a known pdf and is, with good approximation, uncorrelated from pixel to pixel.

With reference to the logarithmically transformed data:

$$y(n,m) = \log |z(n,m)|^2 = x(n,m) + e(n,m)\,, \qquad (2)$$

the following denoising scheme was applied to SAR images in [6]:

1. wavelet transform of the data $y(n,m)$;
2. thresholding of the wavelet coefficients;
3. inverse wavelet transform to get the estimate $\hat{x}(n,m)$;

where $e(n,m)$ was assumed to be Gaussian. The accuracy of the estimate depends strongly on: (i) the levels of the wavelet transform, (ii) the threshold and (iii) the thresholding scheme. In our Multiresolution Speckle Reduction Algorithm (MSRA) the hypothesis of Gaussian noise is not required, the number of the resolution levels is chosen according to a statistical analysis of the noise and the thresholding scheme is modified.

In a multiresolution analysis a signal is represented by its component at a coarse resolution and by the detail signals at finer resolutions. Choosing the number of levels in multiresolution signal analysis is equivalent to defining the frequency band of the coarse signal. According to the correlation properties of the backscattered signal, the wavelet coefficients at the higher resolutions should be due mainly to the noise, while the signal contribution becomes prevalent at lower resolutions. These considerations have led to fix the minimum number of levels of the MSRA according to the statistical characterization of the noise. A rough estimate of the noise can be obtained through a reconstruction using the wavelet coefficients at the high resolution levels, putting to zero the coefficients at the coarse resolution. In absence of signal, the noise estimate improves as we increase the number of levels, while, in presence of signal, it improves once the noise wavelet coefficients are not exceeded by the signal wavelet coefficients. The goodness of the estimate is measured by means of a Kolmogoroff-Smirnov test [10] between the Empirical Cumulative Distribution Function (ECDF) of the estimated noise and the known theoretical CDF:

$$F_e(x) = 1 - \exp\{-e^{x-\gamma}\} \qquad (3)$$

where γ is the Euler's Constant, and the noise is, without loss of generality, zero-mean. By estimating the noise and performing the Kolmogoroff-Smirnov test at every resolution level, it is possible to measure the signal contribution in the wavelet coefficients. The coarse resolution level should be chosen not higher than the one giving the minimum Kolmogoroff-Smirnov distance, corresponding to the best noise estimate, since the noise contribution is not negligible in the wavelet coefficients at higher levels.

In [5] the threshold was chosen according to a minimax risk criterion or, alternatively, the universal threshold $\sigma\sqrt{2\log n}$ was used, where σ^2 is the noise variance and n is the number of data points; in both cases the underlying hypothesis is that the noise is Gaussian. In the case of SAR images the Gaussian hypothesis is not valid but the threshold can be still chosen according to the noise variance. More precisely, the Tchebycheff's inequality [10]

$$\Pr\{|X - \mu_X| \geq k\sigma_X\} \leq \frac{1}{k^2}\,, \qquad (4)$$

where X is a random variable, μ_X and σ_X its mean and standard deviation, respectively, applied to the noise wavelet coefficients, allows the choice of a threshold $k\sigma$ such that every sample in the wavelet transform in which the underlying signal is zero will be less than the threshold with high probability. Obviously, σ is the standard deviation of the noise wavelet coefficients and, if the transform is orthonormal, it is always the same at every resolution level. From the noise CDF given in Eq. 3, it can be shown that the input noise variance is $\sigma^2 = \pi^2/6$. The knowledge of the statistical model eliminates the problem of the variance estimation [6].

As to the thresholding scheme, in the MSRA a new method has been proposed as improvement of the *soft* thresholding, introduced in [5] and applied to SAR images in [6]. In the *soft* thresholding, generalized to non-orthonormal transforms by the introduction of a threshold depending on the resolution level, the coefficients $\hat{w}_j^x(n,m)$ of the signal estimate are:

$$\hat{w}_j^x(n,m) = sgn(w_j^y(n,m))(|w_j^y(n,m)| - t_j)_+\,, \qquad (5)$$

where $w_j^y(n,m)$ are the wavelet coefficients of the noisy input $y(n,m)$, t_j is the threshold, depending on the resolution level 2^{-j}, with $j = 0$ corresponding to the input resolution, and $sgn(\cdot)$, $(\cdot)_+$ are the signum function and the linearly rising function, respectively.

According to Eq. 5, the wavelet coefficients whose modulus are lower than the threshold are put to zero, since they are assumed to be the noise coefficients. Actually, this is not always the case, because, even in presence of signal, the coefficients could be lower than the threshold. The probability that the wavelet coefficients contain the signal rises as we lower the resolution level, corresponding to lower frequency bands where, according to the signal correlation properties, it is more likely to find the texture information. So, a new thresholding scheme, where the coefficients of the signal estimate are corrected by adding an amount proportional to the index j, is now proposed. The estimate coefficients, in the MSRA, become:

$$\hat{w}_j^x(n,m) = \begin{cases} sgn(w_j^y(n,m))(|w_j^y(n,m)| - (1-\frac{j-1}{N})t_j) \\ \qquad\qquad\qquad\qquad \text{if } |w_j^y(n,m)| > t_j \\ \frac{j-1}{N} w_j^y(n,m) \qquad\qquad \text{otherwise} \end{cases} \quad (6)$$

where N is the number of levels. It is quite intuitive, and proved experimentally in the next section, that, due to the additive term, the new thresholding scheme preserves quite well the signal structure, and further, given the minimum number of levels, the reconstruction is much less depending on the choice of the coarse resolution level than in the previous scheme.

4 EXPERIMENTAL RESULTS

The MSRA was tested on both simulated random sequences with assigned statistical properties, and ERS-1 SAR images. The initial aim was to compare the signal estimate obtained by the MSRA and the minimum mean sqare error (MMSE) linear estimate obtained by a Wiener filter. Random sequences were generated according to the statistical model given by Eq. 1, with a K-distributed amplitude, a characterization widely accepted for the description of the sea clutter in many cases of interest. K-distributed sequences $z(n)$ were obtained by generating the noise $g(n)$ as an uncorrelated Gaussian sequence and the signal $s(n)$ as a correlated sequence with a $\mathcal{X}$ pdf, so that the signal intensity results in a Gamma-distributed texture corrupted by an exponential distributed speckle. The Wiener filter, the soft thresholding algorithm and the MSRA were applied to the transformed sequence $y(n)$ given by Eq. 2. The simulation environment allows the estimation of the correlation functions $r_{xy}(m)$ and $r_y(m)$ involved in the Wiener-Hopf equation [10] for the evaluation of a FIR Wiener filter:

$$r_{xy}(m) = \sum_{k=-M}^{M} h_o(k) r_y(m-k), \quad \forall m \in [-M, M] \quad (7)$$

where $x(n)$ and $y(n)$ are the signal to be estimated and the input signal respectively, and $h_o(k)$ is the Wiener filter. It is interesting to notice that, even if the MSE is comparable to the one of the Wiener filter in both the soft and the new thresholding methods, in the former the resulting estimate is a smoothed version of the original signal, while in the latter the estimate is very close to the Wiener one. Table 1 shows the MSE values corresponding to the Wiener filter, the soft thresholding scheme of Eq. 5 and the new thresholding scheme of Eq. 6, evaluated for three different simulations corresponding to three different values of the shape parameter ν of the Gamma pdf. The MSRA performance in term of MSE is generally better than the soft thresholding scheme performance. In Figure 1 graphics of estimates obtained from the three different algorithms show the strong similarity between the optimum linear estimate resulting from the Wiener filter and the MSRA estimate, while the soft thresholding scheme gives a smoothed version of the signal.

	Wiener	Soft Thresh.	MSRA
$\nu = 0.5$	0.4492	0.6025	0.5315
$\nu = 1.5$	0.3445	0.4707	0.3840
$\nu = 3$	0.2304	0.3214	0.3631

Table 1. MSE for Wiener filter, soft thresholding scheme and MSRA

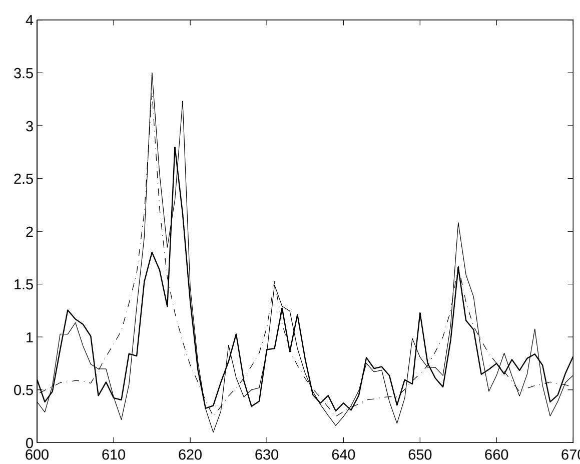

Fig. 1. Signal estimates obtained from the Wiener filter (bold solid), the MSRA (solid) and the soft thresholding scheme (dot-dash)

The three algorithms were applied to some C-band ERS-1 SAR images. Figure 2(a) shows the original single-look image of a region of the Eolie Islands (Italy) where the speckle effect is quite evident. Figures 2(b) and 2(c) are the denoised images obtained from the MSRA and the soft thresholding method, respectively. The improvement introduced by the MSRA is

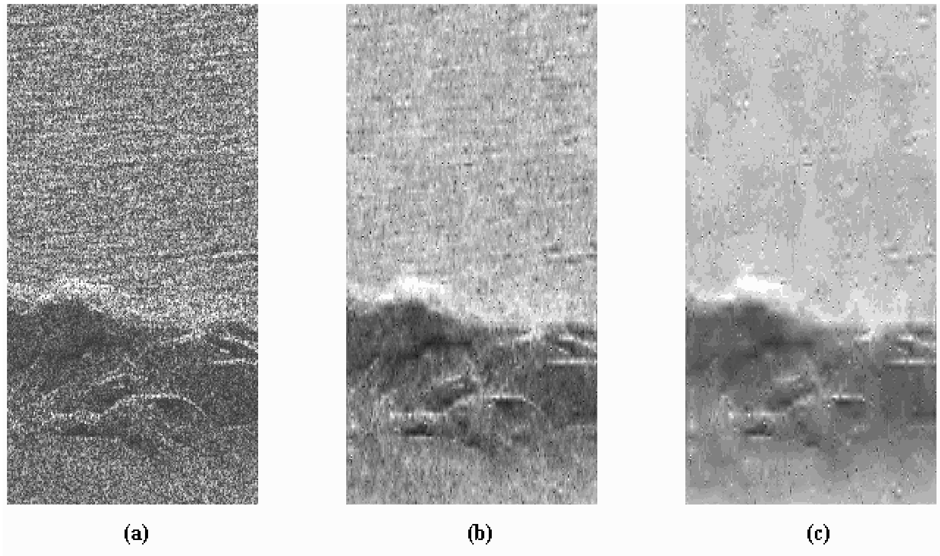

Fig. 2. (a) Original ERS-1 SAR image, (b) MSRA processed image, (c) Soft thresholding processed image

now proved by simple visual inspection of the two processed images: in the image 2(b) the speckle is reduced and edges, as the island coast, and sharp features, as the swell pattern, are preserved, while in the image 2(c) it is evident that, even if the speckle is greatly reduced, the edges have been smoothed as well. As to a quantitative analysis, a parameter used to evaluate the performance of speckle reduction algorithms is the equivalent number of looks, ENL, [3] or the standard deviation to mean ratio, std/m = $ENL^{-1/2}$, used as a measure of the speckle strength [1, 6]. With reference to the ERS-1 image under test, an initial value ENL=0.94 has been estimated on the original image, while the value measured on the image processed by MSRA is ENL=17 corresponding to the order of an equivalent multi-look processing for speckle reduction. It is worth noticing that the ENL is a good measure of speckle reduction in homogeneous regions, but it does not give indication about the ability of preserving edges, as confirmed by the value ENL=240 measured on the image 2(c). The analysis of the experimental results has proved the superiority of the new algorithm, which yields a good speckle reduction with an improvement in the edges preservation and without resolution loss.

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